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A review on the basics of building energy estimation

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ABSTRACT

Energy security, environmental concerns, thermal comfort, and economic matters are driving factors for the development of research on reducing energy consumption and the associated greenhouse gas emissions in every sector of the economy. Building energy consumption estimation has become a key approach to achieve the goals on energy consumption and emissions reduction. Energy performance of building is complicated since it depends on multiple variables associated to the building characteristics, equipment and systems, weather, occupants, and sociological influences. This paper aims to provide an up-to-date review on the basics of building energy estimation. Regarding models, a classification for energy estimation models is proposed based on the different classifications found in the literature review. The paper focuses on models developed with whole building energy simulation software and their validation. This focus is justified because of the importance that whole building energy tools have gained on areas such as green building design, and analysis of energy conservation strategies and retrofits. Since a suitable weather file is a major component for reliably simulations, the section about weather data provides pertinent information.

Contents

1. Introduction

Energy consumption of the residential sector averages approximately 30% worldwide [1]. In the U.S., the residential sector accounts for 22.2% of the total energy (primary energy consumption, electricity retail sales, and electrical system energy losses) consumption when compared with the 18.5%, 31.4%, and 27.8% of the commercial, industrial, and transportation end-use sectors respectively [2]. Therefore, forecasting energy consumption at the design stage or analyses of retrofit options is important for energy and emissions reduction efforts. Since energy consumption is a function of a great amount of information regarding (a) building characteristics, (b) energy systems characteristics, control and maintenance, (c) weather parameters, and (d) occupants' behavior, among other sociological parameters, forecasting buildings energy consumption is not an easy task. In this sense, a lot of efforts from the scientific community, governments, and industry have originated multiple research efforts that have given origin to several approaches and methods as well as multiple tools for estimation of building energy performance. The Building Energy Software Tools Directory [3] is a comprehensive list of tools grouped in four subjects: whole building analysis; codes and standards; materials, components, equipment, and systems; and other applications. These subjects show that efforts can go from a specific component affecting the energy use such as equipment (e.g. condenser of the heat pump) to the whole building analysis.

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In this paper, when a particular information is given, it refers to applications developed or/and adopted in the U.S., with particular interest in residential buildings.

Countless papers related to approaches used on building energy estimation can be found in academic databases. For example, recent works on regression analysis approaches include [4–9] and on machine learning approaches include [10–13]. These references illustrate examples on the use of the approaches on predicting energy consumption. However, this paper focuses on the basics of whole building energy estimation and not in any particular approach. On the other hand, this paper considers only approaches that have been used for whole building energy estimation at the design stage of new buildings or for analysis of energy conservation measures and retrofit; it does not consider approaches used in energy management oriented to control of building performance or performance of building's component or systems [14,15]. It is also important to mention that similar or the same approaches may be used for energy demand analysis or energy models [16–19], but this subject is outside the scope of this paper.

The information on the basics of whole building energy estimation is presented in four sections that are justified as follows. The literature review showed that there is no unique structure for the classification of the information available regarding the different approaches on building energy estimation. In Section 2, the author has tried to summarize several of the criteria found. Calibration is an important procedure to determine the accuracy on the estimation of the energy performance. Therefore, in Section 3 material regarding experiences and procedures for calibration are considered. Calibration requires actual data that in general is not available. However, for certifications such as the Home Energy Rating System (HERS), software meeting some verification criteria is accepted to produce satisfactory energy estimations. Section 4 summarizes some references regarding this matter. For all models the input parameters dealing with weather should be the same when models want to be compared, calibrated, or validated. Thus, in Section 5 information on weather data for energy estimation (energy simulations) is covered.

2. Classification

In this section, the author has tried to use the effort of other authors regarding the review of previous publications on the different approaches used for whole building energy simulation. Therefore, this section is developed based on five comprehensive reviews [1,20–23]. A capital letter and a number inside of curly brackets after an approach described in the references consulted is used in Table 1 to point correspondence with the classification proposed by the author in Fig. 1.

The 2009 ASHRAE Handbook [20] has a broader category based on two approaches.

- *Forward* (*classical*) *approach*: in this approach the equations describing the physical behavior of systems and their inputs are known and the objective is to predict the output. Accuracy increases as models become more complex and as detail information on the building is known {A1}.
- *Data-driven* (*inverse*) *approach*: in this approach input and output variables governing the performance of the systems have been measured. The known data is used to define a mathematical description of the system. The data can be nonintrusive or intrusive. The intrusive data refer to data gathered under controlled experiments. When operation of the building limits the implementation of controlled experiments, nonintrusive data is gathered from normal operation.

For both approaches, forward and data-driven, the models can be steady-state or dynamic. Steady-state models do not consider the transient effect of variables and is good for analysis in time steps equal or greater than 1 day. Dynamic models are able to track peak loads and are useful to capture thermal effects such as those obtained from setback thermostat strategies.

The data-driven approach includes three categories.

- *Empirical or "Black-Box" Approach*: this approach uses a simple or multivariable regression analysis to find the relationship between the outputs and inputs parameters such as climate data, occupancy behavior, and operation parameters {A2}.
- *Calibrated Simulation Approach*: this approach implies the use of a simulation computer program that has been calibrated with actual measured data, allowing the model to predict the energy consumption satisfactorily {A3}.
- *Gray-Box Approach*: this approach uses a two steps development. First a mathematical model is developed for the physical configuration of the building and/or systems/equipment having relevant impact on energy consumption. Then, statistical analyses are used to identify and quantify the parameters that can allow the model to estimate energy performance satisfactorily.

A list of methods based on this classification is given in Ref. [20] {A4}.

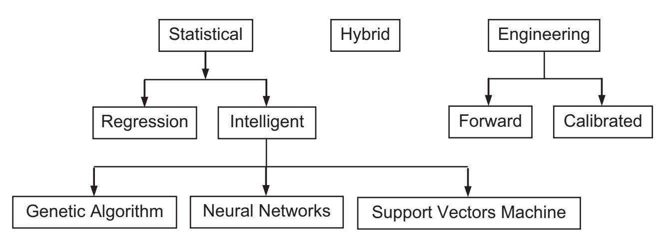


Fig. 1. Classification for energy estimation models.

Table 1
Correspondence of approaches on references with the proposed classification.

Ref.	Statistical				Hybrid	Engineering	
	Regression	Intelligent				Forward	Calibrated
		Genetic algorithm	Artificial neural networks	Support vector machine			
[20]	{A2}				{A4}	{A1}	{A3}
[1]	{B1}					{B2}	
[21]	{C2}		{C3}	{C4}	{C5}	{C1}	
[22]	{D1}	{D3}				{D2}	
[23]	{E2}				{E3}	{E1}	

Swan and Ugursal [1] introduce two main categories based on the reference to the hierarchal position of data inputs as compared to the housing sector as a whole.

- *Top-down approach*: this approach considers the overall energy consumption of the residential sector. This involves information on energy consumption as the one given by the U.S. Energy Information Administration. This approach is used to identify factors defining changes in energy consumption trends on the long-term.
- *Bottom-up approach*: this approach accounts for models considering small samples with similar characteristics that later can be used to extrapolate the results to identify a segment of the residential sector.

In this paper only the bottom-up approach is of interest. Therefore, the two groups of methods discussed by Swan and Ugursal on the bottom-up approach are of interest.

- *Statistical methods*: these methods use historical data on energy consumption and any kind of regression analysis to identify the source of the energy consumption from particular end-uses. The authors define three sub-groups: regression, conditional demand analysis, and neural networks {B1}.
- *Engineering methods*: these methods use equipment and systems and/or heat transfer and thermodynamic relationships to account for end-uses energy consumption {B2}.

Zhao and Magoulès [21] present five groups for prediction methods.

- *Engineering methods*: methods that use physical principles to estimate energy performance at the building or component level {C1}.
- *Statistical methods*: methods developed to correlate historical energy consumption data or energy indexes with data of the variables governing the energy consumption {C2}.
- *Neural networks*: artificial neural networks, as artificial intelligence, are used to solve nonlinear problems to predict building energy consumption {C3}.
- *Support vector machines*: methods of machine learning that are effective in solving nonlinear problems even with small quantities of training data {C4}.
- *Gray models*: models developed when the information of the system is partially known or due to the uncertainty of the data {C5}.

Pedersen [22] defines three methodologies to categorize load and energy estimations.

- *Statistical approaches/regression analyses*: these approaches are mainly based on linear or multivariate regression analyses that use large amount of metered energy consumption data to generate results with high statistical significance {D1}.
- *Energy simulation programs*: these programs uses weather data and detailed building characteristics to simulate the building energy performance in "… an attempt to emulate the reality" {D2}.
- *Intelligent computer systems*: systems developed based on machine learning algorithms that are capable of "make decisions" based on an interpretation of data {D3}.

A most recent review done by Foucquier et al. [23] suggests three main categories with common approaches for each one.

- *Physical models*: this category includes the Computational Fluid Dynamics approach, the Zonal approach, and the Multizone or the Nodal approach. For the focus of this paper, the Multizone approach is of interest since it is the approach used in common simulation software such as EnergyPlus [24], ESP-r [25], TRNSYS [26], and e-QUEST [27]. In comparison with the other two approaches in this category, the Multizone approach considers that the properties defining the thermodynamic state of each building thermal zone are homogeneous over the entire volume {E1}.
- *Statistical methods*: this category refers, when compared to the physical approaches, in the fact that the approaches in this category do not require physical information about the building or systems. This category includes Multiple Linear Regression or Conditional Demand Analysis, Genetic Algorithm, Artificial Neural Network, and Support Vector Machine {E2}.
- *Hybrid models*: this category refers to approaches that combine elements of physical approaches and statistical approaches, which are also called "grey box." These kind of approaches try to overcome the limitations of physical approaches on the need to know detailed information on building physical characteristics, and the limitations of statistical approaches regarding the need of considerable amount of measured data and the difficulty to associate results to physical concepts {E3}.

Fig. 1 illustrates the classification proposed by the author summarizing the classifications given by the references consulted. Some comments are needed for the justification of this classification.

- The hybrid approach is considered at the same category of statistical and engineering approaches because the hybrid approach is a combination of both, "… a physical model to represent the structure or physical configuration of the building or HVAC&R equipment or system, and then identifies important parameters representative of certain key and aggregated physical parameters and characteristics by statistical analysis [20]."
- The statistical approach is divided in two sub-categories (regression and intelligent) to account for methods purely statistical (e.g. simple linear and multiple linear regressions) and methods involving learning or training algorithms.
- The engineering approach has two sub-categories (forward and calibrated) to distinguish models based on the use of measured data for validation. The forward sub-category refers to models accounting for natural phenomena affecting system behavior and overall performance, but they have not been calibrated with actual measured data. The forward sub-category includes models developed for specific buildings that although has not been calibrated with measured data, their results are considered to be validated through the verification status of the tool/method used (see Section 4). The calibrated sub-category refers to models that have been calibrated using actual measured data.
- The steady-state or dynamic characteristic is intrinsic to the models regarding if the model accounts for delay in heat gain and losses due to thermal mass, variation in equipment/system efficiency due to partial load, and any other input affecting the energy performance for time analysis of one hour or less.

The approaches found in the references used in this section have been used to generate Table 1 which shows the corresponding approaches based on the proposed classification of Fig. 1.

The accuracy of an approach depends on the information that is available for the purpose of the approach. Statistical approaches need measured data but not buildings characteristics, while the forward engineering approaches need building characteristics but not data, at least that a calibrated model is the goal. Therefore, for the question of what approach is better, the answer depends on

Table 2
Suitability of approaches (S: satisfactory and G: good).

Approach	Application		
	Design	ECM	Retrofit
Regression	N/A	S	S
Intelligent	N/A	S	S
Hybrid	N/A	S	S
Forward	G	G	S
Calibrated	N/A	G	G

what type of the information is available and in what magnitude. For example, Hernandez and Sanzovo [28] compared results from an EnergyPlus model as a forward engineering model and a feed-forward artificial neural network approach. Results were similar with some large errors on the forward approach mainly related to proper evaluation of schedules for lighting, equipment, and occupancy. Based on the lack of an accepted methodology for comparing approaches, information on when an approach could be used is more useful. Therefore, Table 2 is proposed as a reference on the suitability (satisfactory or good) of an approach based on the scope of the paper on approaches used for new buildings design, analysis of energy conservation measures (ECM), and analysis of retrofits.

3. Calibration

"The process of fitting the model to the observed data by adjusting the parameters is known as calibration [29]." This definition was given in a general context, but this section focuses on models for building energy consumption, and in particular with whole building energy simulation models which fall into the calibrated engineering models as per in Fig. 1. Therefore, the following definition is more appropriate "Calibrated simulation is the process of using an existing building simulation computer program and "tuning" or calibrating the various inputs to the program so that observed energy use matches closely with that predicted by the simulation program [30]." The focus of this section is based on the common use of whole building energy simulation programs for the analysis of energy-conservation and energy-efficiency measures. Some statements supporting this orientation are (a) "… an existing building simulation computer program and "tunes" or calibrates the various physical inputs to the program so that observed energy use matches closely with that predicted by the simulation program. Once that is achieved, more reliable and insightful predictions could be made than with statistical approaches [30]"; (b) "Reducing the energy use of existing homes offers significant energy-saving opportunities, which can be identified through building simulation software tools that calculate optimal packages of retrofit measures [31]"; (c) "Simulation is commonly held to be the best practice approach to performance analysis in the building industry [32]"; and (d) "Ideally, whole-building energy simulation programs model all aspects of energy use and thermal and visual comfort in buildings. …, an essential component of the development of such computer simulation models is a rigorous program of validation, testing, and diagnostics [33]," "Energy simulation models play a key role in computing potential energy savings from retrofits [34]," "Simulation provides a mechanism to determine where savings opportunities exist or energy inefficiency occurs in a building [35]," and "Calibrated simulation is also very useful, facility professionals who can benefit from the availability of a model to explore energy saving potentials as well as ECM impacts [36]." In this sense, the whole-building energy performance simulation tools sponsored by the U.S. Department of Energy are EnergyPlus (a new-generation building energy simulation program from the creators of BLAST and DOE-2), DOE-2 (DOE-2.1E, an hourly, whole-building energy analysis program which calculates energy performance and life-cycle cost of operation), Building Design Advisor (provides building decision-makers with the energy-related information they need beginning in the initial, schematic phases of building design through the detailed specification of building components and systems), and SPARK (models complex building envelopes and mechanical systems that are beyond the scope of EnergyPlus and DOE-2) [3].

Reddy [30] presented a detailed literature review of calibrated simulation techniques, describing their strengths, weaknesses, and applicability. The references consulted by Reddy where grouped as follows:

- calibration based on manual, iterative, and pragmatic intervention,
- calibration based on a suite of informative graphical comparative displays,
- calibration based on special tests and analytical procedures, and
- analytical/mathematical methods of calibration.

Among the six purposes mentioned by Reddy regarding the use of calibrated simulations, one is directly related to the focus of this paper. In this sense, Reddy suggests that calibrated models support the analysis of investment-grade energy conservation measures allowing an accurate estimation of their payback.

Having Reddy's comprehensive review as a reference of previous work done, pertinent work found to be published after Reddy's review is given in this section.

Raftery et al. [32] described a five steps approach for calibration: (1) preparation (initial model, historical weather data, calibration data, documentation), (2) obtain readily accessible data and information, (3) update model inputs (zone-typing, constructions, HVAC and plant, internal loads), (4) error check, and (5) iterative calibration process (test model for acceptance, review outputs using visualization techniques, investigate possible further sources of information, update model). They point out that although the methodology is intended to apply to detailed calibration studies with high resolution measured data, the primary aspects of the methodology (evidence-based approach, version control, and zone-typing) are independent of the available measured data. For the case study, they used EnergyPlus as the whole building energy simulation software. The results showed excellent correlation with a mean bias error of −4.2% for the HVAC electrical consumption data.

Ryana and Sanquist [37] presented a narrative review of the validation of building energy models under idealized and realistic conditions. Validations under idealized conditions seek to validate the coupled physics of the models and the engineering assumptions. In idealized cases, test cells are often modeled. A test cell is an experimental arrangement that can be useful when trying to isolate the effects of specific building features in order to define how the model predict different parameters and how the parameters are correlated with each other. In realistic validation studies building energy models are compared to metering and auditing data. In realistic validation, validation of the physics behind the models is sought, but also the methods used to account for the occupants and their behavior. In general, realistic validation methods attempt to verify the accuracy of building energy models under a variety of conditions where the effects of the occupants need to be included in the model.

Heo et al. [34] point out that whole building transient simulation models such as EnergyPlus can be used to model a building and its control systems which are important when some characteristics or

parameters need to be evaluated within the context of overall energy consumption of the building. However, they also suggest that to compare cost-benefits of competitive retrofit technologies at the macro-level, the level of detail that a simulation program demands is often not necessary. Therefore, they propose that a Bayesian approach can potentially allow the use of lower resolution models to be used without compromising the degree-of-confidence in the outcomes. The authors conclude that the case study considered demonstrates that the proposed methodology can correctly evaluate energy retrofit options and support risk conscious decision-making by explicitly inspecting risks associated with each retrofit option.

Ahmad and Culp [35] developed a test protocol with constraints on available resources, including time, simulation skill, and simulation software. In their approach, they used measurements covering building energy use over several years; the data were not made available until after the simulation results using the software DOE-2.1E were completed. As per the result of the data and simulations results comparisons, they concluded that when the total energy for the building was calculated, discrepancies in the range of ±30% were observed, and in general, uncalibrated simulations were observed to result in discrepancies from the measured data exceeding ±90% for individual components such as chilled water or hot water.

Pan et al. [36] describe the methodology and results of a calibrated building energy model to be used for evaluation of energy performance and cost-effectiveness of energy conservation measures. They used three different measurements and verification approaches to define the acceptable tolerance for monthly data calibration. For the development of the model they used the DOE-2.1E as the simulation engine. In their approach they use the “refine model” step to revise the model inputs when the model was not satisfactorily calibrated. After calibration, the mean bias error index (used for comparisons of monthly energy use) decreases from ±39% to ±7.1% and from ±82% to ±13.1% for electricity and gas respectively.

Westphal and Lamberts [38] presented results of a case study of their six stages methodology for calibration of building simulation models. The methodology was tested using EnergyPlus, and sensitive analysis was applied considering the linearity effect of the input parameters. In each step different parameters were adjusted and for the final model the higher monthly difference was 20%, with the annual energy electric consumption estimated by simulation was only 1% lower than recorded value.

Reddy et al. [39] proposed a general methodology of calibrating detailed simulation programs. The methodology is deeming to be methodical, rational, robust, and computationally efficient while being flexible enough to satisfy different users with different personal preferences and biases. Their approach advocates that it is much more robust to identify a small set of most plausible solutions instead of the “best” solution. This is justified since the calibration of a detailed energy simulation program involving numerous input parameters is a highly underdetermined problem. Thus, a satisfactory overall calibration to the utility billing data will not guarantee accurate identification of the individual parameters in the simulation program. The main idea behind each steps are (1) prepare a preliminary simulation input file of the building that is as realistic and error-free as possible; (2) reduce the dimensionality of the parameter space by resorting to walk-through audits and heuristics; (3) identify the more sensitive or strong parameters by performing a “bounded” coarse grid calibration using a Monte Carlo simulation involving numerous trials with different combinations of input parameter values; (4) perform a guided search calibration to further refine or improve on the calibrated solutions identified by the coarse grid search; and (5) use a small number of the most plausible solutions for a more robust prediction of the energy and demand reductions. In a further description of the methodology, six elements of the calibration methodology are discussed. The first five elements are directly associated to the five steps of the methodology, but the last one refers to the computation of uncertainties in the calibrated model prediction.

Coakley et al. [40] used a four steps methodology for calibration of an engineering model developed using EnergyPlus [24]. The steps can be described as follows. (1) Data Gathering/Building Audit refers to gathering building geometric data, weather data, HVAC systems specifications, and detailed load/occupancy schedules; (2) Evidence-Based Building Energy Simulation (BES) Model Development refers to an initial construction of the model and an iteratively update of the model based on information acquired on a continuous basis; (3) Bounded Grid Search refers to an statistical calibration based on a Monte Carlo method to define range of variation for unknown input variables based on data classification; and (4) Uncertainty Analysis refers to the process of ranking the solutions based on statistical goodness-of-it (GOF) criteria since more than one solution may satisfy the objective function.

In a more general context, Building Energy Simulation TEST (BESTEST) is a method for testing, diagnosing, and validating the capabilities of building energy simulation programs. The BESTEST validation standard has been under development by the National Renewal Energy Laboratory (NREL) since the 1980s. A list of related documents is available for download on the NREL publications database. From the BESTEST Test Suites, the BESTEST for existing homes (BESTEST-EX) [41] is commented in this review. BESTEST-EX is a test procedure that allows software developers to evaluate their audit tools' performance in modeling energy use and savings in existing homes when utility bills are available for model calibration.

BESTEST-EX includes two kinds of test cases: building physics test cases with fully known inputs, and calibrated energy savings test cases with specified base-case monthly utility bill data and uncertainty ranges for selected inputs. The building physics test cases are a direct application of software-to-software comparative test methods. A given audit model is tested using specified inputs; BESTEST-EX compares software simulation findings to reference results generated with state-of-the-art simulation tools such as EnergyPlus, SUNREL, and DOE-2.1E [41]. Utility bill calibration test cases, after running the building physics cases, diagnosing results disagreements, and correcting all found modeling errors, a given audit model (and associated calibration methods) can be tested by comparing utility-bill-calibrated energy savings predictions to results from the reference programs [42]. The BESTEST-EX base building is based on HERS BESTEST [43]. “Typical building descriptions and physical properties published by sources such as DOE, the National Association of Home Builders, the American Society of Heating Refrigerating and Air-Conditioning Engineers (ASHRAE), and the National Fenestration Rating Council (NFRC) are used for the test cases [43].”

Most of the work done at the NREL in conjunction with the International Energy Agency is the content of the ASHRAE Standard 140 [44]. The standard specifies tests procedures for evaluating the technical capabilities and ranges of applicability of computer programs that calculate the thermal performance of buildings and their HVAC systems. The tests should allow identifying and diagnosing predictive differences that may possibly be caused by algorithmic differences, modeling limitations, input differences, or coding errors. The current set of tests included consists of (1) comparative tests that focus on building thermal envelope and fabric loads and mechanical equipment performance and (2) analytical verification tests that focus on mechanical equipment performance. The scope of the standard establishes that while the standard test procedures cannot test all algorithms

within a building energy computer program, they can be used to indicate major flaws or limitations in capabilities.

To finalize this section, the OAK REDGE National Laboratory is developing the Autotune methodology [45,46] for calibrating building energy models (BEM). Autotune is aimed at developing an automated BEM tuning methodology that enables models to reproduce measured data such as utility bills, sub-meter, and/or sensor data accurately and robustly by selecting best match input parameters for the software EnergyPlus (or other simulation and energy audit tools) in a systematic, automated, and repeatable fashion. The methodology is based on a multiobjective optimization via sensitivity analysis; data mining to provide automated mapping between available data and model input variables; application of a suite of machine learning algorithms to generate calibration functions; and quantification of trade-off between tuning accuracy and amount of data available.

4. Verification

In the U.S. residential sector, the Residential Energy Services Network (RESNET) [47] sets the Nation's standards for Home Energy Efficiency. RESNET is responsible for creating the national training and certification standards for Home Energy Rating System (HERS) raters and home energy survey professionals. The HERS and certified professionals are recognized by federal government agencies such as the U.S. Department of Energy, the U.S. Environmental Protection Agency and the U.S. mortgage industry. HERS rating gives an index that measures home's energy efficiency. The index is obtained by comparing the home energy use against a reference home. To obtain the house's energy use to be compared with the reference home (reference house's energy use), a whole building energy simulation program is used. The software used by HERS raters must be verified and accredited by RESNET. For a software to be accredited by RESNET, it must satisfy the requirements set out on the Procedures for Verification of RESNET Accredited HERS Software Tools [48]. The verification process is based on the satisfaction of the test suite adopted by the RESNET Board.

- ANSI/ASHRAE Standard 140-2011, Class II, Tier 1 Tests: the ANSI/ASHRAE Standard 140-2011, Class II, Tier 1 test procedure has been adopted by RESNET and is a requirement for all software programs to be accredited.
- HERS Reference Home autogeneration tests: these tests verify the ability of the software tool to automatically generate the HERS Reference Home.
- HERS method tests: these tests verify that software tools can accurately calculate the HERS Index that is used as the numerical indicator of relative performance for a home.
- HVAC tests: these tests verify the accuracy and consistency with which software tools predict the performance of HVAC equipment, including furnaces, air conditioners, and air source heat pumps.
- Duct distribution system efficiency tests: these tests verify the accuracy with which software tools calculate air distribution system losses. ASHRAE Standard 152 results are used as the basis for the test suite acceptance criteria.
- Hot water system performance tests: these tests determine the ability of the software to accurately predict hot water system energy use.

Although “there is no such thing as a completely validated building energy simulation computer program. All building models are simplifications of reality [44],” verification is a valid practice to accept results from simulation programs when compared to a reference. Therefore, although a model developed using accredited software is not a calibrated model; its results are assumed to be accurate enough to be considered valid.

5. Weather data

Weather parameters are some of the most important factors that influence the load and energy demand on buildings. For whole building energy simulations, a suitable weather file is a major component that allows reliably analysis of energy savings from energy management practices and retrofits. Weather stations usually record many weather parameters, but some are more important than others for building energy consumption. For example, for simple regression analysis models the outdoor temperature is the parameter used, and for multiregression analysis usually no more than three weather parameters are used.

Pedersen [22] addresses weather files for thermal load and energy estimations in buildings with a focus on European sources. In this paper, the focus is on weather files/formats used in the U.S. and mainly by the EnergyPlus software [24]. The EnergyPlus' site has a webpage for “Weather Data for Simulation.” In this webpage it is stated that “Users of energy simulation programs should avoid using single year, Test Reference Year-type (TRY) weather data.” The Typical Meteorological Year (TMY) and Weather Year for Energy Calculations (WYEC) are recommended because these formats reproduce a year that can predict energy consumption and energy costs that are closer to the long term average. This webpage recommends a paper by Crawley [49] for more information on selecting weather data appropriate for energy simulation. In Ref. [50], Crawley et al. present more detail on the “E/E” weather format used by EnergyPlus and ESP-r, as two of the major simulation programs in the U.S. and Europe, respectively. This format is based on data available within the TMY2 weather format. An important difference between EnergyPlus/ESP-r (E/E) format and TMY2 is a minute data field. The minute data field is used for data measured at intervals of less than 1 h which facilitates calibration of models when data is available. For EnergyPlus, the E/E format is identified as EPW. In order to translate typical weather data into the EPW format, Crawley et al. [50] developed a utility that is available on the EnergyPlus software. As examples on the use of this formats, verification procedures for HERS software tools are based on TMY weather file format, with Colorado Springs, Colorado (a clear, cold climate) and Las Vegas, Nevada (a hot, dry climate) as two locations for the test [51], and ASHRAE Standard 140 uses TMY weather files to perform tests.

Typical Meteorological Year version 3 (TMY3) data sets are an update to, and expansion of, the TMY2 data released by the National Renewable Energy Laboratory (NREL) in 1994 [52]. Because they are based on more recent and accurate data, TMY3 data sets are recommended for use in place of earlier TMY2 data.

For calibration of building energy models weather data matching the recording time of energy consumption is necessary. These weather data should include all of the variables which have a significant effect on the building and should be measured at the building itself where possible [32]. When on-site data is not available, other resources must be used to have a measured data as close to the site as possible. The webpage “Real-Time Weather Data” from the EnergyPlus website, allows to obtain real-time data that can be useful for calibration purposes. Another source, with a link on the EnergyPlus website, is Weather Analytics [53]. This site can provide TMY files or Actual Meteorological Year (AMY) files (delivered in the same file formats as TMY files). The use of data recorded by a weather station not located close enough to the site may introduce error due to the influence of microclimates conditions. For example, Bhandari et al. [54] investigated the impact of

discrepancy in various weather parameters and heating/cooling loads from two different sources of data. The heating/cooling loads were obtained from simulations results of a model developed with EnergyPlus [24]. The two sets of data correspond to third-party weather data and data collected from a weather station inaccessible to the service providers. The results showed that the peak difference in individual hourly variables can be as high as 90%, and annual building energy consumption can vary by $\pm 7\%$ while monthly building loads can vary by $\pm 40\%$ for different weather data sets.

When using actual weather data, the user should be aware on how the model/software handles the weather parameters. For example, EnergyPlus corrects air density based on barometric pressure. However, if the program being tested does not use barometric pressure from the weather data, correction for the change in air density due to altitude should be accounted. Another example is how the model/software handles time. Weather data is recorded on local time, but solar computations are based on solar time.

6. Conclusion

Building load and energy estimation is an approach that is gaining continuous importance for the analysis of projects oriented to energy consumption and emissions reduction. A review on the basics of building energy estimation was done considering models, calibration, verification, and weather files. Models fall in three major categories: statistical, gray-box, and engineering. Calibrated engineering models developed with whole building energy simulations tools have gained particular interest because they allow for reliable simulations of options to investigate their energy savings and emissions reduction potential. Typical meteorological year weather files are the format been adopted by the major simulation software such as EnergyPlus (in U.S.) and ESP-r (in Europe). Verification procedures as required for the accreditation of software tools used for HERS rating use TMY weather files and make results from simulations to be trusted without using actual weather data.

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